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Abstract

Big data analytics (BDA) adoption is a game-changer in the current industrial environment for precision decision-making and optimal performance. Nonetheless, the determinants or consequences of its adoption in small and medium enterprises remain unclear; hence the objective of this study. Data analysis of 171 Iranian small and medium manufacturing firms revealed that complexity, uncertainty and insecurity, trialability, observability, top management support, organizational readiness, and external support have a significant effect on BDA adoption. The findings confirm the strong impact of BDA adoption in small to medium-sized enterprises, marketing and financial, performance enhancement. Understanding the drivers of BDA adoption helps managers to employ appropriate initiatives that are vital for effective implementation. The results enable BDA service providers to attract and diffuse BDA in small to medium-sized enterprises.

Keywords: big data analytics adoption; technological-organizational-environmental model; Small to Medium-sized Enterprises; Firm performance

1. Introduction

Big data analytics (BDA) has transformed the way businesses compete (Müller, Fay, & vom Brocke, 2018). It presents new techniques in extracting hidden patterns from a set of raw information for making correct decisions, increasing productivity, generating knowledge, and upgrading innovations (Acharya, Singh, Pereira, & Singh, 2018; de Vasconcelos & Rocha, 2019; Yaqoob et al., 2016). Generally, big data represents employees' and customers' interactions stored in the organization's system (Calvard & Jeske, 2018; Shirdastian, Laroche, & Richard, 2019) which provides actionable, descriptive, predictive, and prescriptive results" (Lamba & Dubey, 2015, p. 5). As it is characterized according to its volume, velocity, and variety (structured and unstructured) (Calvard & Jeske, 2018), extracting valuable knowledge and information from big data remains a complex activity.

Previous studies have indicated that BDA enables firms to improve their performance and allows them to benefit from the adoption of BDA (Ghasemaghaei, 2018; Mikalef, Boura, Lekakos, & Krogstie, 2019; Mikalef, Krogstie, Pappas, & Pavlou, 2019; Nam, Lee, & Lee, 2019; Raguseo, 2018; Raguseo & Vitari, 2018). Considering the benefits of BDA, many large firms have adopted it for different purposes, such as predicting new trends in the market and evaluating customers' behaviour and experiences to identify new opportunities for improvement (Mandal, 2018). Though small to medium-sized enterprises (SMEs) are key for a nation's economy, they are lagging far behind in the usage of BDA (Coleman et al., 2016). The lack of understanding of and limited resources for big data among SMEs are the main barriers of BDA adoption (Christina & Stephen, 2017; Coleman et al., 2016; Sen, Ozturk, & Vayvay, 2016; Shin, 2016). Maroufkhani, Wagner, Wan Ismail, Baroto, and Nourani (2019) systematically reviewed the studies on BDA and found that studies on the drivers of BDA adoption among SMEs are scarce. So, this study draws on the technological-organizational-environmental (TOE) model in investigating the drivers of BDA adoption among SMEs. The strength of the TOE model lies in its flexibility in explaining the level of technology adoption among firms (Grant & Yeo, 2018; Tsou & Hsu, 2015).

Extensive research on the impacts of TOE factors on the adoption of various technologies are available in the literature (Chandra & Kumar, 2018; Hsu & Lin, 2016). However, the findings cannot be directly applied and generalized to BDA adoption in SMEs because the influence of TOE factors depends to the type of technology, size of firms, and country of study (Alharbi, Atkins, & Stanier, 2016; Ghobakhloo, Arias-Aranda, & Benitez-Amado, 2011; Wang, Jin, & Mao, 2019). Every technology has its unique characteristics and various factors affect its successful adoption (Wang et al., 2019). Further, Gangwar, Date, and Raoot (2014) reviewed the empirical studies on technology adoption and found different TOE factors for adopting different technologies. For instance, although compatibility is a significant driver of knowledge management and radio frequency identification (RFID) adoption, it has no significant effect on enterprise resource planning (ERP) and electronic data interchange (EDI) adoption. Furthermore, the impacts of TOE factors vary with firm size and that findings of studies on large firms cannot be generalized to SMEs (Ghobakhloo, Arias-Aranda et al., 2011; Themistocleous et al., 2005). The significant difference between resource availability, organizational structure, technological infrastructures and environmental situations of SMEs and large firms affects the importance of TOE factors in adopting the technology. As such, a new model is needed to understand the drivers of BDA among SMEs. Alharbi et al. (2016) stated that the variation of country requirements and environmental situations determine the extent to which TOE factors affect the level of adoption of technology in a firm and consequently hence the need to consider individual cases.

Ghasemaghaei (2018) argued that not all firms investing in BDA could improve their performance. However, the majority of the studies have scrutinised the influence of BDA on the performance of large corporations, and there is dearth of empirical studies regarding its effect on the performance of SMEs (Raut et al., 2019; Wamba et al., 2017; Wang, Kung, Wang, & Cegielski, 2018). This study aims to explore the effect of BDA on SMEs' performance. This study addresses the following questions:

1- What technological, organizational and environmental factors influence the extent of BDA adoption among SMEs?
2- Does BDA adoption influence financial performance and market performance of SMEs?

The findings of this study contribute to the body of knowledge by illustrating the antecedents and outcomes of BDA adoption among SMEs in a single framework which is used as a BDA adoption model for SMEs. Furthermore, the results enable managers/ owners of SMEs to understand the factors involved in successfully adopting BDA and help policymakers to promote BDA among SMEs.

2. Literature review

Rapid development in social networking, advanced mobile technologies, e-commerce websites, search engines and other types of new digital technologies (Surbakti, Wang, Indulska, & Sadiq, 2020) has led to the surge of big data. Big data creates the opportunity for firms to generate and capture data which are characterized by three Vs (Russom, 2011); Volume, Variety, and Velocity. Volume refers to the vast amount of data collected by firms to discover hidden information and pattern in data and to gain critical knowledge (Ghasemaghaei, 2020) while Variety represents the different formats of data which managing them by the traditional analytic system is complicated. These data include unstructured, semi-structured, and structured data (Mohapatra & Mohanty, 2020). On the other hand, Velocity indicates the speed of generating and analysing the data in real-time (Jeffrey Kuo, Lin, & Lee, 2018; Shukla, Yadav, Kumar, & Muhuri, 2020).

Mikalef, Pappas, Krogstie, and Giannakos (2018) stated that the meaning and concepts of big data, BDA, and BDA capabilities (BDAC) vary, though some researchers used these terms interchangeably. The same authors systematically found that some studies concentrated on the data and its characteristics whereas others develop the definition by including the term of analytics which its emphasis is on the process, tools and techniques required to analyse the data. Once the focus moves to the impact of hidden values of big data extracted by the analytical techniques, the definition of BDAC may arise. Dubey, Gunasekaran, and Childe Stephen (2019) argued that the features of big data (volume, velocity, and variety) force companies to put much effort to catch meaningful insight from it as the traditional techniques of analysis do not work for analysing such data.

The notion of BDA refers to the advanced techniques such as data-mining, visualizing, and sense-making for organizations to analyse the big data (Grossman & Siegel, 2014). According to Mikalef et al. (2018), the techniques are wide-ranging, so, we argue that the success of big data is dependent on BDA practices. Further, organizational resources such as data-driven culture and organizational learning must exist for transforming big data into practical values. Therefore, to address this issue, the term of BDAC has taken place as it makes firm able to successfully implement big data and take advantage of its business values (Mikalef et al., 2018).

BDA has become a stimulus that can maximize the efficiency and effectiveness of firms due to its high operational and strategic benefits (Ji-fan Ren, Wamba, Akter, Dubey, & Childe, 2017; Wamba et al., 2017). Corporations applying big data techniques should alter data into intelligence and understandable visions, thus ameliorating their performance (Chen, Preston, & Swink, 2015; Maroufkhani et al., 2019). As such, BDA could enhance a firm's performance by improving the firm's agility as it increases the speed of processes to accomplish tasks (Ghasemaghaei, Hassanein, & Turel, 2015). Ji-fan Ren et al. (2017) argued that the lack of a relationship between BDA investment and firm performance was mostly due to the unavailability of appropriate data, as the business value generated from such investments was missing. Wamba et al. (2017) stated that all the business values created through BDA could be examined by taking the resource-based view theory (RBV) into account. RBV can explain the relationship between resources/capabilities and organizational performance based on the characteristics of a firm or the quality of the resources and capabilities they have for innovation (Barney, 2014; Ji-fan Ren et al., 2017).

BDA has significant influences on the performance of firms within different industries (Wamba et al., 2017). The majority of retailing corporations are leveraging big data capabilities to develop a customer-management relationship. In the healthcare industry, BDA is likely to enhance business values as it enables more accurate medical decisions (Rajabion, Shaltooki, Taghikhah, Ghasemi, & Badfar, 2019; Wang et al., 2018). In other sectors, such as manufacturing, BDA could sustain firm performance (Raut et al., 2019; Rehman, Chang, Batool, & Wah, 2016) and that it has become a facilitator for the improvement of supply chain management (Gunasekaran et al., 2017; Mandal, 2018). Some studies argue that the impact of BDA adoption on financial and firm performance (Akter, Wamba, Gunasekaran, Dubey, & Childe, 2016; Wamba, Akter, Edwards, Chopin, & Gnanzou, 2015; Wamba et al., 2017). The next section explains the theoretical foundations of the study.

3. Theoretical background and hypotheses development

The theoretical foundations are the technology-organization-environment (TOE) model, the diffusion of innovation theory (DOI), and RBV. Drawing on the RBV theory, this study attempts to scrutinize the theoretical relationship between BDA and firm performance where BDA adoption is seen as a capability in firms and is considered an intangible resource. Obtaining new knowledge or skills leads a firm to have a better technological capability, in particular, BDAC, and as a result, better performance (Galetsi, Katsaliaki, & Kumar, 2020). Following RBV, Gupta and George (2016) argued that what makes organizations able to build the BDAC are the resources of the organization. Organizational resources are tied to the firm's ability to collect and take the ultimate advantage of its resources. Further, Dubey et al. (2019) believed that BDAC could be considered as a facility for the organization in terms of tools, techniques, and processes by which the firm could be able to process, and analyse data, consequently make proper operational decisions.

According to Mikalef, Krogstie et al. (2019) and Gupta and George (2016), to create BDAC, organizational resources would be classified to employees' big data-related skills, tangible, and intangible types. As an example, data and technology are tangible resources and organizational learning and data-driven culture of an organization make up intangible resources. Mikalef, Krogstie et al. (2019) stated that intangible resources are important as they may broaden the horizon of the decision-makers and increase their knowledge for sound decisions. According to Dubey et al. (2019, p. 2014), "the information derived via BDAC provides firms with real-time information," so, organizations can perform better (Gupta and George, 2016; Wamba et al., 2017; Akter et al., 2016). Inspiring previous studies on BDAC, the present research considers the whole term of BDAC as an intangible resource which without it, companies are not able to adopt an innovation successfully. In this light, BDAC could be a positive force to form the culture of a firm. Then, it can encourage firms to use big data for different purposes such as improving operations, ameliorating decision making, and sustaining competitive advantage and firm development (Kwon, Kwak, & Kim, 2015; Wang & Hajli, 2017).

Scholars (e.g., Piaralal, Nair, Yahya, & Karim, 2015; Alshamaila, Papagiannidis, & Li, 2013) have stressed that integration of the TOE and DOI theories provides the best-fit factors for the context of technology adoption in SMEs. DOI precisely emphasizes technological characteristics as drivers for technology diffusion and the process of diffusing technology adoption throughout the firm (Chiu, Chen, & Chen, 2017). Similarly, the TOE model covers all inner and outer factors which may influence the adoption of technology among firms, while DOI focuses mostly on technological elements (Chiu et al., 2017; Zhu, Kraemer, & Xu, 2006). Kapoor, Yogesh, and Michael (2014) stated that considering technology implementation aspects is essential in innovation adoption studies. Therefore, incorporating the technological factors of DOI theory into the TOE model can deliver a comprehensive framework for this study, and it makes Rogers' DOI theory better able to illuminate the diffusion of intra-firm innovation (Hsu, Kraemer, & Dunkle, 2006). Drawing on the developing literature on BDA and its business values and the TOE factors for the adoption of technology, the current study proposes the conceptual model (Figure 1) using the TOE model and the DOI and RBV theories. A wide range of TOE factors has influenced the adoption of technology. This study examines the technological (relative advantage, compatibility, complexity, uncertainty and insecurity, trialability, and observability), organizational (top management support and organizational readiness) and environmental (competitive pressure, external support from vendors, and government regulation) factors. The researchers presents rationale for the proposed hypotheses in the following subsections.

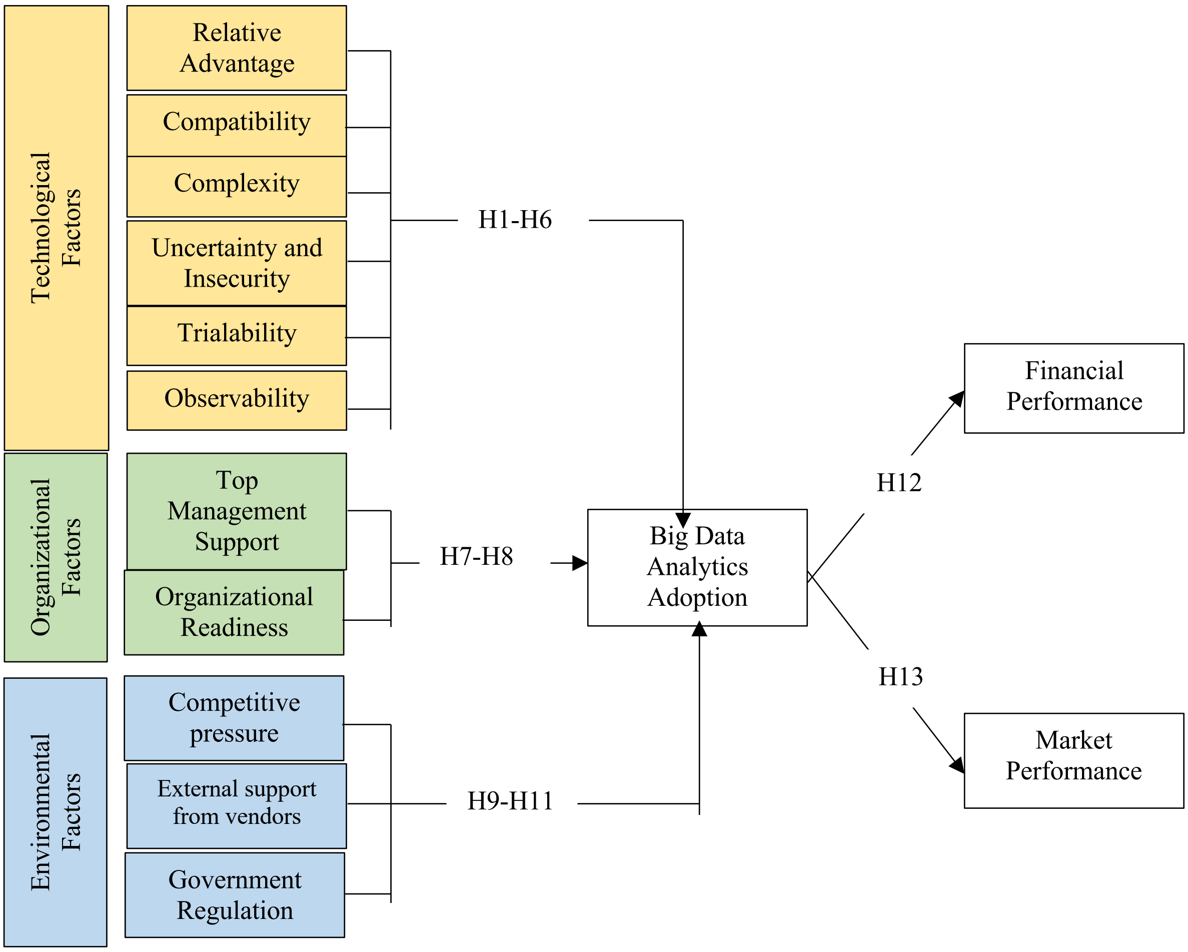

Figure 1. Empirical Model

3.1. Technological context

The technological context explains the endogenous and exogenous elements of a technology that are critical for its adoption. One of the elements is relative advantage (Baker, 2012; Kapoor, Dwivedi, & Williams, 2015) in which the intention of most organizations may be profoundly affected by the perceived advantage that new technology can add to the particular performance of an organization (Gu, Cao, & Duan, 2012). The relative advantage is considered as the extent to which the adoption of technology (e.g., BDA) is perceived as being better than other types of technology or the current technology used in businesses and what advantages it may have for the company (Rogers, 2003). Ghobakhloo, Arias-Aranda et al. (2011) and Ullah and Qureshi (2019) argued that among SMEs are willing to adopt a technology if they perceive that its advantages outweigh the advantages of the existing technology. As such, the study suggests the following hypothesis.

H1. The relative advantages of BDA have a positive relationship with its adoption.

According to Awa (2017), compatibility examines the degree to which a new system is consistent with the current system within the company. The compatibility of technology adoption reflects its congruity with the culture and business practices of an organization (Chen et al., 2015). Kapoor, Dwivedi, and Williams (2014) found compatibility as one of the significant drivers of technology adoption. Further, Verma and Bhattacharyya (2017), Chen et al. (2015), and Gangwar (2018) have empirically evidenced that compatibility is one of the key influential determinants for BDA adoption. However, to have a positive link between compatibility and BDA adoption, firms can increase their flexibility in terms of policies and procedures (Gangwar, 2018). As such, this study suggests that SMEs are more willing to accept and implement it in various parts of their organization if they recognize that the BDA adoption is compatible with current organizational procedures and standards. This study proposes the following hypothesis.

H2. There is a positive relationship between Compatibility and BDA adoption.

Rogers (2003) testified that the adoption of new technology or system might fail if it is perceived as being too ambitious and challenging to implement. Challenges exist, for example, in altering the processes in which they work together, so, the new technology must be easy to use to enhance the chance of adoption (Alshamaila et al., 2013; Kandil, Ragheb, Ragab, & Farouk, 2018). Employees must quickly acquire knowledge about the new technology as the more sophisticated the technology, the more uncertainty and the more complex the process of adoption will be. Studies have demonstrated that complexity is a substantial factor in the adoption of an innovation (Harindranath, Dyerson, & Barnes, 2008; Kandil et al., 2018), thereby, decision-makers are in a dilemma about adopting the innovation (Asiaei, 2019; Ghobakhloo, Arias-Aranda et al., 2011). Compared to other technological elements of innovation, complexity links negatively with the adoption of new technology (Alshamaila et al., 2013; Huynh, Huy, Rowe, & Truex, 2012). The recent literature on the role of complexity in the adoption of BDA has found that the complexity of big data negatively influences its adoption (Gangwar, 2018; Lai et al., 2018). Thus, if SMEs perceive that adoption of innovation requires considerable effort, they are less likely to adopt it. The researchers suggest the following hypothesis.

H3. Firms that perceive a high level of complexity of BDA have a low level of willingness to adopt BDA.

According to Alshamaila et al. (2013), uncertainty is considered as the risk that may accompany the adoption of an innovation, and this risk is a barrier to maintaining the innovation in the current system of the organization. For the adoption of data-related innovation, security and privacy are among the most common concerns (Asiaei, 2019; Aziz, 2010). For example, (Alshamaila et al., 2013) indicated that cloud computing innovation is hugely reliant on the degree of uncertainty. Recent studies on technology innovation have also highlighted the importance of security concerns about big data and the need to rectify the deficiency of such a discussion in past studies (Ghasemaghaei, 2020; Raguseo, 2018; Sun, Cegielski, Jia, & Hall, 2018). As discussed above, the cloud is a host for big data; therefore, the issue of privacy and security that is inextricably linked with the nature of cloud computing and data has been taken as a predictor of BDA adoption (Gangwar, 2018; Lai et al., 2018; Raguseo, 2018; Raut, Priyadarshinee, Gardas, & Jha, 2018). Indeed, it is argued that the main concern of business owners when the issue of the adoption of data-related services comes up is privacy and security (Priyadarshinee, Raut, Jha, & Kamble, 2017). From this perspective, the security concern also refers to the risks inherent in outsourcing. The risk is linked to the use of third-party tools and assistance to provide a BDA solution or the adoption of cloud computing services (Asiaei, 2019; Priyadarshinee et al., 2017).

Generally, firms willing to benefit from the advantages of big data in their businesses may need to outsource the entire initiative of big data or a part of it. For example, most firms outsource the job because, first, they still suffer from the insufficient capability to build and sustain a big data environment within their businesses, and second, they need support due to the newness of big-data-related innovations (Wood, 2013). However, the requirement of outsourcing may raise the issue of security or privacy. Since outsourcing requires firms to share their data with vendors and external suppliers, there is a risk of firms losing control over their information. This study believes that the factor of uncertainty and insecurity is intensively influential for the adoption of BDA; hence, the following hypothesis is proposed.

H4. Organizations that perceive a high level of uncertainty and insecurity of BDA have a low level of willingness to adopt BDA.

Trialability is the degree to which an IT innovation is promising to be tried (Laurell, Sandström, Berthold, & Larsson, 2019). It is one of the key factors for early adopters including SMEs because, from the initial stage, they know the effectiveness of the innovation (Alshamaila et al., 2013; Moghavvemi, Hakimian, Feissal, & Faziharudean, 2012; Ramdani & Kawalek, 2007). Therefore, it is an opportunity for early innovators to shrink the level of uncertainty (Rogers, 2003). According to Wu and Corbett (2019), the quicker the innovation is exposed, the faster it is adopted. Jeyaraj, Rottman, and Lacity (2006), and Asare (2016) stressed that trialability is the most vital antecedent that affects the adoption of the internet and new online technology among academics. This study proposes that if SMEs were able to try the BDA innovation, the possibility of adopting and maintaining such a new technology innovation could be higher. This study hypothesizes the following.

H5. Trialability has a positive impact on the adoption of BDA.

Observability is "the degree to which the results of an innovation are visible to others" (Rogers, 2003, p. 258). While observability promotes innovation adoption within firms (Kapoor, Yogesh et al., 2014), it is the only element of technological context found not to positively affect the adoption of IT techniques in SMEs (Ramdani & Kawalek, 2007).

Following the controversy, this study proposes that if BDA adoption is visible for the owners of SMEs, the SME's owners are more likely to adopt BDA in their businesses, hence the following hypothesis is developed.
H6. The observability of BDA technology has a positive connection with the adoption of BDA.

3.2. Organizational context

Management support and organizational readiness have been considered in this study to be the attributes that affect SMEs' BDA adoption. Top management support refers to the degree to which managers comprehend and embrace the technological capabilities of a new technology system (e.g., BDA) (Sanders, 2008). According to Jahanshahi and Brem (2017), the decision-makers in SMEs are very likely to be in the top management team, and their support is critical for the adoption of an innovation. Indeed, they are the main link between individual and organizational technology adoption, as the tendency for adoption relates to the level of top managers' or leaders' innovativeness. Previous studies by Chen et al. (2015), Cruz-Jesus, Pinheiro, and Oliveira (2019) and Alshamaila et al. (2013) have found top management support as a critical determinant of successful innovation adoption. In the context of SMEs, top managers were less willing to implement new systems (Asiaei, 2019; Ramdani & Kawalek, 2007, 2008), thus, based on the preceding argument, the following hypothesis is proposed.
H7. Top management support is positively linked with BDA adoption.

Organizational readiness is the ability and the willingness of firms to adopt new technology (Gangwar, 2018). It represents the firm's capability to manage and invest in the adoption of new technology including technical IT capability and expertise (Taxman, Henderson, Young, & Farrell, 2014; Yoon & George, 2013). In the area of business analytics and big data, there is a harmony between academics that organizational readiness is a prerequisite to BDA implementation (Gangwar, 2018; Ramanathan, Philpott, Duan, & Cao, 2017). In the context of SMEs, Asiaei (2019) and Ghobakhloo, Arias-Aranda et al. (2011) reported that organizational readiness has a significant and positive relationship with the adoption of new technology. Given that, this study proposes that organizational readiness is one of the most critical conditions or requirements for BDA adoption; therefore, the following hypothesis is proposed.
H8. Organizational Readiness positively influences BDA adoption.

3.3. Environmental context

Environmental factors are those elements that organizations may confront with their external boundaries (Xu, Ou, & Fan, 2017). Within the environmental context, firms are usually more delicate to the dynamic external ecosystem. Hence, under the TOE model, competitive pressure, external support, and government regulations represent the external elements that may influence SMEs' adoption of BDA. Based on the definition developed by Chen et al. (2015, p. 18), competitive pressure refers to "influences from the external environment that prompts the organization to use BDA". It is the pressure that comes to a firm from its customers, suppliers, and competitors. In the context of SMEs, Ghobakhloo, Arias-Aranda et al. (2011) and Asiaei (2019) reported that the more firms are under pressure to compete, the more new technology is expected to be successfully adopted. Based on a review by Grandon and Pearson (2004), five out of ten studies they conducted revealed that competition significantly influences technology adoption in SMEs. Besides, according to

Aboelmaged (2018), environmental burdens from the media, competitors, and customers significantly affect sustainable manufacturing practices (SMP) in Egyptian SMEs, while environmental regulations do not. Some scholars believed that the increasing usage of BDA by competitors could motivate the owners and managers to successfully and professionally capture business intelligence and analytics to uphold the firm's competitive position in the market place (Chen et al., 2015; Lautenbach, Johnston, & Adeniran-Ogundipe, 2017). Therefore, this study hypothesizes the following.
H9. Competitive pressure positively influences BDA adoption.

External support is referred to the extended support from a vendor or third-party to encourage firms to innovate and able to adopt an innovation (Biney, 2019; Gangwar, 2018). It is one of the crucial drivers of innovation success, which can positively influence innovation adoption (Ghobakhloo, Arias-Aranda et al., 2011; Ren, Ngai, & Cho, 2010). Receiving external support from vendors is a substantial attribute for BDA adoption, as firms can develop their innovation capabilities by learning from vendors and available open-source platforms (Gangwar, 2018). To the best of the authors' knowledge, outsourcing from external parties and vendors works exceptionally well for SMEs, as they do not have sufficient technical skills to adopt an innovation such as BDA. So, using available platforms and training programs may increase their capabilities for the adoption. Based on this perspective, the current study develops the following hypothesis.
H10. External support from vendors is positively associated with BDA adoption.

Government regulation is implemented in terms of promotions and restrictions, and sometimes, these regulations may encourage firms to adopt a particular type of new technology (Stieninger & Nedbal, 2014; Tornatzky, Fleischer, & Chakrabarti, 1990). According to Lai et al. (2018), government rules and policies in terms of encouragement, technological standards, and legislation can increase the adoption of BDA among firms. For instance, Hsu, Ray, and Li-Hsieh (2014) and Lai et al. (2018) found that firms encountering a high level of regulations and pressure from the government are more likely to adopt cloud technology. This study also follows the recent literature of BDA adoption and considers that government regulations in terms of support and incentives stimulus the BDA adoption. Accordingly, this study proposes the following hypothesis.
H11. Government regulation positively influences BDA adoption.

3.4. BDA adoption and financial performance

Prior evidence about BDA and its business values showed that BDA impact significantly on financial performance (Akter et al., 2016; Wamba et al., 2017). BDA techniques can increase a firm's return on investment (Akter et al., 2016), or accomplishment of the e-commerce buying process (Jayanand, Kumar, Srinivasa, & Siddesh, 2015) which eventually increase the sales and income of firms. Hofmann (2017) stated that BDA solutions or applications provide stronger financial outcomes. In this line, Raguseo and Vitari (2018) found a positive relationship between BDA implementation and firm's financial performance even under high levels of market turbulence and environmental changes as far as it can increase customer's satisfaction and loyalty, growth of sales and profitability.

Although investment in BDA adoption might be costly, any input for improving the BDA assets and capability will lead to significant improvements in the productivity of firms (Müller et al. 2018). Yang, See-To, and Papagiannidis (2020) found that the predictive power of BDA

enables an organization to deliver business models by which they can generate more revenues. Ji-fan Ren et al. (2017), Raguseo and Vitari (2018), and Wamba et al. (2017) indicated that BDA adoption would likely help companies enhance their financial performance. Yasmin, Tatoglu, Kilic, Zaim, and Delen (2020) went further by saying that BDA tends to improve a firm's financial performance rather than market performance. Accordingly, the current study expects that SMEs that adopt BDA will gain higher levels of financial performance. Therefore, we suggest the following hypothesis.
H12. BDA adoption positively influences firm financial performance.

3.5. BDA adoption and market performance

BDA applications enable organizations to efficiently manage and utilize the hidden values of big data for better decision-making and innovation activities (Baesens, Bapna, Marsden, Vanthienen, & Zhao, 2016) and marketing strategies (Lycett, 2013). By adopting BDA, firms can leverage customers' engagements in the business and thereby improve their market performance (Saldanha, Mithas, & Krishnan, 2017). Market performance is the ability of firms to deliver a higher degree of market share, to enter new markets as quickly as possible, to introduce new products and services regularly with a higher rate of success (Vitari & Raguseo, 2019). Dong and Yang (2020) claimed that BDA would create massive value for firms and increase their market performance through better decisions about innovation and marketing strategies (Dong & Yang, 2020).

Adopting BDA can improve a firm's dynamic capability, in a way that permits firms to detect the opportunities and risks in the market, use the possible chances to seize a considerable portion of the market, and improve the new products and services with the technological advancement (Côrte-Real, Oliveira, & Ruivo, 2017; Davenport, 2014; Shirazi & Mohammadi, 2019). Efficient use of the organization's capabilities and resources such as BDA would enhance the firm's competitive advantage and consequently, its marketing performance (Raguseo & Vitari, 2018). Once companies increased their competitive advantage in the market, they could improve their market performance in terms of market share, market development, and sales of growth (Chakphet, Saenpakdee, Pongsiri, & Jermittiparsert, 2020). Previous researchers also found that advanced solutions of BDA can improve the marketing positions of companies since its applications enable firms to identify the market opportunities and threads much faster than before. Therefore, organizations can outline, determine and identify the most appropriate market, marketing strategies, product, and service by the lens of BDA techniques (Vitari & Raguseo, 2019). Accordingly, the study suggests the following hypothesis.
H13. BDA adoption positively influences firm market performance.

4. Methodology

4.1. Measurements

The researchers adapted a previously validated survey questionnaire to collect data. The measurement items and their relative sources are shown in Appendix. Following the arguments from previous studies (Dwivedi, Kapoor, Williams, & Williams, 2013; Shareef, Dwivedi, Kumar, & Kumar, 2017; Sharma & Sharma, 2019), the study used a five-point Likert-type scale with anchors ranging from 1 ('strongly disagree') to 5 ('strongly agree') except for market performance and financial performance. The two performance constructs were measured using a five-point Likert-type scale ranging from 1 ('much worse than major competitors') to 5 ('much worse than major competitors'). The draft version of questionnaire was pretested by three academicians and two BDA experts from the industry. Based on their inputs, the questionnaire was revised and used for the pilot study. As the medium of communication in Iran is Persian, the instrument was translated (into the Persian language) by a language professional and checked by experts in SMEs in Iran. The translated version was reviewed by two other experts to make sure that the aim of the questions is correctly associated with SMEs. The back-to-back translation of the questionnaire maintains the consistency of each item's meaning. Before collecting data from a larger population, the translated version of the questionnaire were piloted with 32 owners/managers of SMEs to ensure the understandability of the survey and to evaluate the reliability of the constructs (Dwivedi et al., 2013; Kapoor, Dwivedi, Niall, Lal, & Weerakkody, 2014). The Cronbach's alpha of all the constructs were above 0.7, indicating relatively good construct reliability (Hair, Black, Babin, & Anderson, 2010).

BDA adoption is conceptualized as a second-order construct and refers to four business values (strategic value, transactional value, transformational value, and informational value) that BDA may produce for SMEs. The items of this section were adopted from Raguseo and Vitari (2018) where Strategic value refers to the degree of perceived benefits to the organization at the strategic level while Transactional value is the degree to which the user perceives that BDA provides operational benefits. On the other hand, Transformational value refers to the degree of perceived changes in the structure and capacity of a firm as a result of BDA, which catalyzes future benefits while Informational value is the degree to which the user of BDA solutions benefits from better information.

The TOE constructs include technological factors, organizational factors and environmental factors. The technological factors comprise of six constructs, namely relative advantage, compatibility, complexity, uncertainty and insecurity, trialability, and observability. The items were adapted from Chen et al. (2015), Ghobakhloo, Arias-Aranda et al. (2011), Premkumar and Roberts (1999), Thong (1999), Tornatzky and Klein (1982), Lai et al. (2018), Xu et al. (2017), Etsebeth (2013), Limthongchai and Speece (2003), Moore and Benbasat (1991), Salleh and Janczewski (2016), and Shin and Shin (2011). On the other hand, two organizational factors, namely top management support and organizational readiness, were included in this study. The measurements of these items were adapted from Chen et al. (2015), Lai et al. (2018), and Priyadarshinee et al. (2017). The environmental factors consist of competitive pressure, external Support, and government regulation. The items were adapted from Lai et al. (2018), Ghobakhloo, Arias-Aranda et al. (2011), Ghobakhloo, Sabouri, Hong, and Zulkifli (2011), Li (2008), Agrawal (2015), and Gupta and George (2016).

The study also includes the dimensions of firm performance to measure the respondents' perception of the effect of BDA adoption on financial and market performance improvement. The measures of these two constructs originated from the studies of Raguseo and Vitari (2018) and Ji-fan Ren et al. (2017). All items of this study and their sources are as shown in Appendix A.

4.2. Sampling and data collection

SMEs in the manufacturing sectors that had adopted BDA form the population of this study. The sampling frame of this study was taken from the Iranian Small Industries and industrial Parks Organizations (ISIPO), which lists a total of 10,931 SMEs in manufacturing sectors in Tehran, Iran. The owner/managers are targeted in this study, as they are assumed to be the main decision-makers for any IT, BDA, and innovation adoption and have sufficient information to answer the questionnaire. We called the target firms to explain the purpose of the study and provide the meaning of BDA. The names and email addresses of the respondents from the firms that agreed to participate in our study were collected. The link of the online survey was sent to the informants of the firms by email. Each survey included a cover letter explaining the research and meaning of BDA. The study has a filter question to ensure that only SMEs that have experience with BDA were included. The respondents were asked, “Does your firm use big data analytics (outsourced are included)?”. A respondent who answered “No” to this question was eliminated from the survey. Of 500 potential respondents, a total of 182 responses were returned after follow-up phone calls at two-week intervals. Out of the 182 responses, 11 were incomplete or not meeting the inclusion criteria, leaving 171 usable questionnaires or a response rate of 34.2%. To assess non-response bias, early and late responses were compared using t-test. The results showed that, at 5% significance level, there was no statistical difference between early and late responses indicating non-response bias is not a concern (King & He, 2005). The researchers also evaluated the Common method bias (CMB) to determine the validity and reliability of underlying constructs and tested relationships in the model (Fuller, Simmering, Atinc, Atinc, & Babin, 2016) using two methods. First, Harman’s single factor test, one of the most common techniques of testing CMB, revealed that the first factor explains 37.62% of the total variance. As a single factor does not carry the majority of the explained variance, CMB is not a serious issue in this study (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). Second, due to limitations of Harman’s single factor in evaluating CMB (Guide & Ketokivi, 2015), the correlations between a marker variable (i.e., “attitude toward buying green products”) and main constructs of the study are evaluated. Again, no significant correlation is detected, indicating that CMB is not a concern (Lindell & Whitney, 2001).

4.3. Data analysis

The proposed hypotheses were analysed using partial least squares (PLS). This technique matches the prediction-oriented character of this study (Hair, Risher, Sarstedt, & Ringle, 2019). Following Hair et al.’s (2019) guideline, the validity and reliability of the variables were tested in the first step of the analysis, followed by structural model analysis.

Table 1 Demographic information of respondents

Characteristic	Frequency	Percentage
Education		
Primary qualification	8	4.7
Secondary qualification	12	7.0
Diploma	56	32.7
Undergraduate degree	90	52.6
Postgraduate degree (Master/PhD)	5	2.9
Age		
18–25 years old	9	5.3
26–33 years old	55	32.2
34–41 years old	63	36.8
42–49 years old	33	19.3
50 years old or older	11	6.4
Gender		
Male	155	90.6
Female	16	9.4
Number of Employees		
1–10 employees	26	15.2
11–49 employees	99	57.9

50–99 employees	34	22.2
100–149 employees	8	4.7
Sector Type		
Food and Beverages	24	14.0
Wood & Wood Products (except furniture)	2	1.2
Chemical	16	9.4
Rubber & Plastic	14	8.2
None-metal Minerals	30	17.5
Basic Metals	19	11.1
Fabric Metals	16	9.4
Machinery & Equipment	24	14.0
Office Equipment	3	1.8
Electrical Machineries & Equipment	11	6.4
Radio, TV& Communication Tools	3	1.8
Optical and Medical Instrumental & Watch	9	5.3
Position		
Executive/Senior manager	70	40.9
Chief executive manager/owner	101	59.1
Big Data Experience		
< 1 year	14	8.2
1–2 years	78	45.6
2–3 years	56	32.2
3–4 years	18	10.5
4+ years	5	2.9

5. Results

5.1 Assessment of measurement model

To assess the convergence of the constructs, factor loadings, composite reliability (CR), and average variance extracted (AVE) were examined. Conceptualizing BDA adoption as a second-order construct, a repeated indicator approach was used. As suggested by Hair *et al.* (2019), the values of factor loadings, CR, and AVE should be higher than 0.7, 0.5, and 0.7, respectively. All the constructs meet the threshold requirements and demonstrate acceptable convergent validity (Table 2).

Table 2. Measurement Model

First-order constructs	Second-order construct	Number of items	Factor loadings	CR	AVE
Relative Advantage (RA)		4	0.754-0.903	0.908	0.713
Compatibility (CMP)		3	0.883-0.893	0.915	0.783
Complexity (CPX)		3	0.880-0.923	0.924	0.802
Uncertainty and Insecurity (UI)		4	0.738-0.855	0.873	0.632
Trialability (TR)		5	0.834-0.875	0.931	0.728
Observability (OB)		5	0.815-0.849	0.920	0.696
Top Management Support (TMS)		4	0.854-0.893	0.929	0.765
Organizational Resources (OR)		4	0.815-0.871	0.900	0.692
Competitive Pressure (CP)		3	0.701-0.928	0.878	0.708
External Support (ES)		3	0.899-0.927	0.941	0.842
Government Regulation (GR)		3	0.797-0.916	0.902	0.756
Informational Value (INV)		3	0.915-0.921	0.955	0.623
Transformational Value (TFV)		4	0.828-0.889	0.942	0.844
Transactional Value (TRV)		3	0.911-0.944	0.923	0.750
Strategic Value (STV)		3	0.897-0.929	0.946	0.854
	Big Data Analytics Adoption (BDA)	4	0.822-0.891	0.928	0.762
Financial Performance (FP)		4	0.763-0.857	0.886	0.661
Market Performance (MP)		4	0.883-0.917	0.942	0.804

Note: CR: Composite Reliability, AVE: Average Variance Extracted

The Heterotrait–Monotrait (HTMT) criteria (Henseler, Ringle, & Sarstedt, 2015) and the Fornell–Larcker criterion (Fornell & Larcker, 1981) were used to evaluate the discriminant validity. As the HTMT values were less than 0.85 (Table 3), the discriminant validity of all given constructs was fulfilled (Kline, 2015). Furthermore, inter-construct correlations were less than the square roots of AVEs (Table 4), indicating good discriminant validity (Fornell & Larcker, 1981).

Table 3. Hetrotrait-Monotrait Ratio ($HTMT_{.85}$).

	RA	CMP	CPX	UI	TR	OB	TMS	OR	CP	ES	GR	BDA	FP	MP
RA														
CMP	0.438													
CPX	0.457	0.560												
UI	0.315	0.402	0.449											
TR	0.376	0.487	0.547	0.356										
OB	0.476	0.560	0.655	0.391	0.509									
TMS	0.453	0.547	0.690	0.421	0.578	0.610								
OR	0.495	0.577	0.789	0.297	0.527	0.743	0.771							
CP	0.160	0.077	0.124	0.070	0.146	0.055	0.080	0.186						
ES	0.273	0.485	0.498	0.396	0.483	0.446	0.395	0.412	0.279					
GR	0.076	0.069	0.075	0.146	0.076	0.062	0.057	0.216	0.589	0.284				
BDA	0.480	0.623	0.784	0.558	0.645	0.719	0.762	0.737	0.077	0.690	0.129			
FP	0.547	0.698	0.780	0.551	0.663	0.754	0.747	0.786	0.057	0.610	0.040	0.769		
MP	0.595	0.691	0.726	0.477	0.752	0.812	0.777	0.840	0.087	0.562	0.108	0.741	0.730	

Note: RA: Relative Advantage; CMP: Compatibility; CPX: Complexity; UI: Uncertainty and Insecurity; TR: Trialability; OB: Observability; TMS: Top Management Support; OR: Organizational Resources; CP: Competitive Pressure; ES: External Support; GR: Government Regulation; BDA: Big Data Analytics Adaption; FP: Financial Performance; MP: Market Performance

Table 4. Fornell and Larcker

	RA	CMP	CPX	UI	TR	OB	TMS	OR	CP	ES	GR	BDA	FP	MP
RA	**0.844**													
CMP	0.381	**0.885**												
CPX	-0.401	-0.487	**0.896**											
UI	-0.266	-0.333	0.378	**0.795**										
TR	0.345	0.431	-0.493	-0.308	**0.853**									
OB	0.421	0.490	-0.580	-0.332	0.466	**0.835**								
TMS	0.406	0.486	-0.613	-0.361	0.528	0.546	**0.875**							
OR	0.431	0.500	-0.685	-0.250	0.468	0.650	0.678	**0.832**						
CP	-0.099	0.063	0.078	-0.050	0.133	-0.015	-0.058	-0.118	**0.839**					
ES	0.248	0.427	-0.444	-0.338	0.442	0.400	0.358	0.364	0.254	**0.918**				
GR	-0.016	-0.055	-0.062	-0.119	0.066	-0.030	-0.017	-0.182	0.474	0.246	**0.869**			
BDA	0.439	0.566	-0.715	-0.488	0.608	0.663	0.707	0.668	0.068	0.642	0.124	**0.789**		
FP	0.468	0.591	-0.667	-0.450	0.582	0.650	0.648	0.666	-0.005	0.529	-0.005	0.774	**0.813**	
MP	0.533	0.615	-0.651	-0.410	0.692	0.734	0.708	0.746	-0.045	0.513	-0.094	0.787	0.727	**0.896**

Note: Diagonal terms (in bold) are square roots of the AVE

RA: Relative Advantage; CMP: Compatibility; CPX: Complexity; UI: Uncertainty and Insecurity; TR: Trialability; OB: Observability; TMS: Top Management Support; OR: Organizational Resources; CP: Competitive Pressure; ES: External Support; GR: Government Regulation; BDA: Big Data Analytics Adaption; FP: Financial Performance; MP: Market Performance

5.2 Assessment of structural model

The researchers used the proportion of variance explained to evaluate the predictive accuracy (R^2) of the theoretical model (Hair et al., 2019). The R^2 values of BDA adoption, financial performance, and marketing performance were 0.783, 0.600, and 0.619, respectively. Furthermore, the Stone-Geisser Q^2 (cross-validated redundancy) value as a measure predictive relevance showed that the Q^2 values of BDA adoption, financial performance, and marketing performance were above zero (Chin, 2010); thus, the model displayed a satisfactory fit.

We applied non-parametric bootstrapping with 5,000 replications (Hair et al., 2019) to assess the structural model. The results (Table 5) showed that complexity (β = -0.168; $p < 0.001$) and uncertainty and insecurity (β = -0.117; $p < 0.01$) have a negative effect on BDA adoption. Furthermore, the positive impacts of trialability (β = 0.102; $p < 0.05$), observability (β = 0.151; $p < 0.01$), top management support (β = 0.231; $p < 0.001$), organizational resources (β = 0.102; $p < 0.05$), and external support (β = 0.264; $p < 0.001$) on BDA adoption were supported. The effects of relative advantage (β = 0.043; $p > 0.05$), compatibility (β = 0.047; $p > 0.05$), competitive pressure (β = -0.008; $p > 0.05$), and government regulations (β = 0.062; $p > 0.05$) were not supported. Furthermore, the results demonstrated that financial performance (β = 0.774; $p < 0.001$) and marketing performance (β = 0.787; $p < 0.001$) were positively influenced by BDA adoption. As such, all hypotheses were supported except H1, H2, H9, and H11.

Table 5. Structural Model Path Analysis

Hypotheses	Relationships	Path Coefficients	St.D	T Values	Decision
H1	RA -> BDA	0.021	0.043	0.501	Not Supported
H2	CMP -> BDA	0.047	0.054	0.868	Not Supported
H3	CPX -> BDA	-0.168	0.054	3.104***	Supported
H4	UI -> BDA	-0.117	0.043	2.742**	Supported
H5	TR -> BDA	0.102	0.054	1.887*	Supported
H6	OB -> BDA	0.151	0.054	2.813**	Supported
H7	TMS -> BDA	0.231	0.053	4.321***	Supported
H8	OR -> BDA	0.102	0.057	1.805*	Supported
H9	CP -> BDA	-0.008	0.044	0.186	Not Supported
H10	ES -> BDA	0.264	0.054	4.845***	Supported
H11	GR -> BDA	0.062	0.054	1.133	Not Supported
H12	BDA -> FP	0.774	0.033	23.117***	Supported
H13	BDA -> MP	0.787	0.027	28.925***	Supported

Note: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$ (one-tail)

RA: Relative Advantage; CMP: Compatibility; CPX: Complexity; UI: Uncertainty and Insecurity; TR: Trialability; OB: Observability; TMS: Top Management Support; OR: Organizational Resources; CP: Competitive Pressure; ES: External Support; GR: Government Regulation; BDA: Big Data Analytics Adaption; FP: Financial Performance; MP: Market Performance

6. Discussion

Among the six technological factors considered, surprisingly, relative advantage and compatibility have no effect on BDA adoption among SMEs. The insignificant effect of relative advantage on BDA adoption is inconsistent with the findings of the study by Gangwar (2018) and Lai et al. (2018) on large firms. The potential reason for the insignificant effect of relative advantage is that in this study, the data were collected from SMEs that had problems in financial, IT infrastructure, and skilled human resources affecting successful BDA adoption. Therefore, knowing the benefits of BDA may not lead to BDA adoption when SMEs lacking financial, IT infrastructure, and skilled human resources.

The insignificant effect of compatibility on BDA adoption contrasts with the findings of Verma and Bhattacharyya (2017) and Chen et al. (2015). The extent of adjustability of SMEs' procedures and practices is the potential reason for the insignificant relationship between compatibility and BDA adoption. As making adjustments and changes within existing business procedures, practices, and values are easier for SMEs in comparison to large firms, compatibility has less effect on the decisions of SMEs' managers to adopt BDA. It shows that the size of these firms enables them to be more flexible, and, consequently, the compatibility between current practices and the BDA system is not a major concern in their decision-making.

Consistent with the findings of Gangwar (2018) and Lai et al. (2018), complexity was found to affect negatively on BDA adoption in SMEs. According to Ismail and Ali (2013) and Asiaei (2019), adopting new technologies may be challenging for SMEs due to the lack of internal expertise. Similarly, the adoption of BDA is difficult for SMEs, and thereby, managers demonstrate a lack of confidence in their firm's skill and ability to adopt BDA successfully. Should this be the case, outsourcing could be a good option for SMEs to adopt BDA.

The negative impact of uncertainty and insecurity on BDA adoption is also confirmed. Previous studies have shown that privacy and security are the main concerns of business owners in adopting data-related technologies (Priyadarshinee et al., 2017). Though BDA outsourcing common among SMEs, losing control of the confidential data and the risk of leaking information to competitors may negatively affect the adoption of BDA. As such, BDA service providers need to gain the trust of SMEs. Often, such trust is derived from the reputation of the service provider or the previous experience of the client with that service provider (Choudhury & Sabherwal, 2003). Bush, Tiwana, and Tsuji (2008) suggested that service providers can create trustworthiness by conveying their reputation for security early and by extensive reliance on referrals from previous clients. Investing in social media marketing is another way of engendering a good reputation (Kim & Ko, 2010).

The significant effect of trialability on BDA adoption is in line with the findings of Asare (2016) and Dwivedi, Papazafeiropoulo, Ramdani, Kawalek, and Lorenzo (2009). Also, Troshani and Lymer (2010) found a significant positive connection between trialability and the diffusion process in different technological contexts. Trials can help firms assess the benefits of adopting technology and reduce the uncertainty of adopting that technology (Ramdani & Kawalek, 2007). Trials also enable firms to understand how to use technology and consequently address the concerns on complexity (Al-Gahtani, 2003; Laurell et al., 2019) and consequently find and solve major problems before launching the technology (Asare, 2016; Wu & Corbett, 2019). As such, BDA service providers should offer a trial version to enhance its adoption in SMEs.

Observability is another technological factor that affects BDA adoption as was confirmed in this study. Bakar, Ahmad, and Ahmad (2019) and Johnson, Friend, and Lee (2017) found a positive relationship between observability and technology adoption. Observing the effective use of new technology by competitors reduces uncertainty and makes SMEs more willing to implement it (Bakar et al., 2019). Thus, as it is difficult for SMEs to predict the value for money of investing in BDA, observing the benefits of BDA adoption in other SMEs can reduce their uncertainty and motivate them to adopt BDA.

The impacts of both organizational factors (top management support and organizational readiness) on BDA adoption among SMEs were confirmed. Top management support is frequently found to be a critical element among SMEs for adopting different types of technology, such as ICT, cloud computing, e-commerce, CRM, and ERP (Alshamaila et al., 2013; Asiaei, 2019; Cruz-Jesus et al., 2019; Ghobakhloo, Arias-Aranda et al., 2011; Ghobakhloo, Sabouri et al., 2011; Ramdani, Chevers, & Williams, 2013). Owners/ managers of SMEs are the primary decision makers, and their vision determines the level of support for BDA adoption. Top management support is a vital element for creating a supportive ecosystem for SMEs to adopt new technologies (Asiaei, 2019; Maduku et al., 2016; Scupola, 2009). Top managers are the stimulators of organizational change by communicating and encouraging values via a well-expressed vision for the firm (Cruz-Jesus et al., 2019; Kandil et al., 2018). Furthermore, the support given by top managers can facilitate the process of the learning and diffusion of technology throughout the firm (Asiaei, 2019). As such, they play a critical role in the different stages of BDA adoption.

The significant linkage between organizational readiness and BDA adoption is compatible with what past studies found on technology adoption in SMEs (Gangwar, 2018; Kandil et al., 2018; Kuan & Chau, 2001; Lai et al., 2018; Ramdani et al., 2013; Wen & Chen, 2010). It is not easy for SMEs to adopt BDA without adequate technological, financial, and skilled human resources. As such, a firm is unlikely to adopt BDA if it does not have the required resources and capabilities. Therefore, financial and initial technological resources are needed to outsource BDA, and skilled employees play an important role in its implementation stage.

Among the three environmental factors (competitive pressure, external support, and government reputation), only external support plays a substantial role in adopting BDA among SMEs. The insignificant effect of competitive pressure is inconsistent with the findings of Dal-woo, Dong-woo and SoungHie (2015) and Ghobakhloo, Sabouri et al. (2011). A lack of multinational competitors and low levels of BDA among local competitors in the Iranian market are the potential reasons for the insignificant effect of competitive pressure in the context of Iran. On the one hand, due to sanctions, multinational firms have not invested substantially in the Iranian market, and, consequently, SMEs in Iran are less affected by globalization. On the other hand, the low rate of adoption of BDA by local firms puts less competitive pressure on SMEs. As such, this factor plays an insignificant role in the decision by owners'/managers' of SMEs to adopt BDA.

The significant relationship between external support and BDA adoption among SMEs is expected and is in line with the findings of Ghobakhloo, Arias-Aranda et al. (2011) and Gangwar (2018). According to Ghobakhloo, Arias-Aranda et al. (2011), if SMEs' CEOs recognize that an IS service provider can satisfy their needs for IS adoption, they are more likely to adopt it. Thus, training and technical support by BDA service providers can address the managers' concern about the lack of technical skills for implementing BDA. As such, external support plays an important role in the decision of SMEs struggling with a lack of human skills.

The findings of this study indicate that government regulations have no effect on BDA among SMEs, which is inconsistent with the findings of Lai et al. (2018) and Ghobakhloo, Sabouri et al. (2011). One potential reason for this insignificant relationship is that SMEs believe BDA adoption is a huge investment and that government incentives will not be sufficient to rationalize the investment. Furthermore, the fast changes in government regulations in Iran hurt the extent to which managers' decisions depend on government regulations, especially in the case of BDA. As such, government regulations have a low effect on SMEs' decision to invest in BDA in Iran.

The results showed that BDA adoption has a substantial effect on both the marketing and financial performance of SMEs. Previous literature found that BDA adoption creates business values for firms and boosts their capabilities (Mikalef, Boura et al., 2019; Müller et al., 2018; Raguseo & Vitari, 2018). According to Müller et al. (2018), BDA has a positive effect on their marketing performance as it enables firms to design products and services that offer superior value for their customers and differentiate them from competitors. Ji-fan Ren et al. (2017) and Raguseo and Vitari (2018) also reported that BDA could increase firms' ability to improve profitability and to gain and keep their customers. BDA enables SMEs to observe the environment via the lens of data; hence, leads them to the best decision outcomes as the information generated by BDA could provide firms with accurate and comprehensive insights (Popovič, Hackney, Tassabehji, & Castelli, 2018). Lee, Lapira, Bagheri, and Kao (2013) concluded that BDA adoption helps manufacturing firms to reduce the level of manufacturing waste and the extra production costs, and prevents faulty product and cut-off to re-product; thus, firms stay superior, and their performance is improved.

6.1 Theoretical contributions and implications

In terms of theoretical contribution, this study answers the questions on the drivers and outcomes of BDA among SMEs. Although there are many studies on BDA adoption among large firms (Wang & Hajli, 2017; Wang et al., 2018), there is a lack of empirical study on SMEs in this context. Maroufkhani et al. (2019) systematically reviewed the studies on BDA and found there is a lack of research on the topic of BDA among SMEs. Since SMEs are different from large firms in terms of the availability of resources and size; therefore, this study aimed to explore the most applicable TOE factors for BDA adoption in the context of SMEs, particularly in Iran. This study provided a single and unique model to evaluate the role of TOE factors on the adoption of BDA and at the same time, examined the impact of BDA adoption on the performance of SMEs. The results of the study showed that complexity, trialability, uncertainty and insecurity, observability, top management support, organizational readiness, and external support play an important role in the decision-making of SMEs' managers/ owners to adopt BDA while relative advantage, compatibility, competitive pressure and government regulation have no effect. The inconsistency of these results with the findings of previous studies on large firms confirmed the existence of differences in drivers for BDA adoption in SMEs and large firms. The findings of this study also prove that BDA has a substantial effect on both the marketing performance and financial performance of SMEs in response to the doubts raised about the benefits of SMEs using BDA.

6.2 Implications for practice

From a practical perspective, the findings have several important implications for managers of both SMEs and BDA service providers. Firstly, the findings provide the support that BDA adoption has a positive effect on market performance and financial performance of SMEs. Despite the extensive discussion on the impacts of BDA on the performance of large firms, a study on the association between BDA adoption and performance of SMEs is still lacking. SMEs are reluctant to invest in BDA due to uncertainty of its payoff and lack of knowledge on the factors that may influence its successful adoption. Our findings confirmed that investment in BDA could improve the performance of SMEs.

Secondly, the results help SMEs' managers understand the factors that need to be considered to successfully adopt BDA. The findings indicate that organizational factors, along with environmental factors and technological factors, can influence the adoption of BDA among SMEs. The decision on the adoption of BDA in Iran is mainly an organizational and environmental driven decision and not technologically driven. The finding can conclude that top management support and external support are among the most critical factors that affect the decision on BDA adoption. The positive effect of top management support, organizational resources, and external support indicates the importance of the supportive role of managers in the whole process of BDA adoption and implementation. Top management provides financial and technical support, acquires skilled employees, provides training for the existing ones, finding the competent BDA service providers and ensures sufficient resources for adopting BDA.

Finally, the significant role of complexity, uncertainty and insecurity, and external support helps BDA service providers to understand the importance of their reputation, especially in security, offering a trial version, and providing effective technical support and required training in promoting BDA among SMEs. The high cost of BDA along with lack of sufficient technical skills make outsourcing as a feasible way of obtaining BDA for SMEs. As complexity and security concerns are two main barriers to adopting BDA by SMEs, BDA service providers should provide a trial version of their service alongside training and technical supports. The reputation and positive word of mouth may signal that the service provider is trustworthy. As such, using social media marketing and referrals might be an effective way of gaining SMEs trust and addressing their security and uncertainty concerns. Furthermore, providing information on the penetration rate of BDA may enhance the visibility of BDA adoption among competitors and consequently motivate SMEs to adopt BDA. The insignificant effects of relative advantage and compatibility indicate that these two factors play a negligible role in shaping the decision of SMEs to adopt BDA. Accordingly, emphasizing on the benefits of BDA and its compatibility should not be the priority of BDA service providers.

6.3. Limitations and future research direction

Like any other empirical studies, there are some limitations of this study that may affect the generalizations of the results. Firstly, the sample population is limited to SMEs, which differ in resources and the flexibility of the structure as compared to large firms. As such, future studies can test this study's model to large firms. Secondly, the study focused on Iran, which is under sanctions at the time of the study. The sanctions have a significant impact on the competitive nature of the market and the government's power in supporting firms' adoption of BDA. Further research is required to test the conceptual framework among SMEs in developing as well as in developed countries. Thirdly, the study is cross-sectional, and hypotheses were tested using a questionnaire survey. This approach limits the ability to demonstrate causality in the relationships among variables. Thus, the results are affected by the fact that the current study could not observe the dynamic changes of BDA adoption. A longitudinal study is needed to test the developed relationships for an extended period to deliver more precise results. Finally, further studies can enrich the conceptual framework of this study by considering other potential factors such as organizational culture, market pressure, and technical infrastructures (Behl, Dutta, Lessmann, Dwivedi, & Kar, 2019; Duan, Edwards, & Dwivedi, 2019; Dwivedi et al., 2017).

7. Conclusions

BDA has increased the efficiency and effectiveness of firms by making organizations depended on the analytical tools for more reliable decisions. Although SMEs are essential for every economy, they are lagging in the usage of BDA (Coleman et al., 2016). Considering the lack of study on the drivers and outcomes of BDA adoption among SMEs, in the light of the RBV and TOE model, the impacts of technological, organizational, and environmental attributes on the adoption of BDA and the effect of BDA adoption on the financial performance and marketing performance of SMEs were investigated in a single and unified framework. The analysis of the literature reveals that the drivers of a technology adoption depend on the type of technology, size of firms, and country of study (see for example, Alharbi et al., 2016; Ghobakhloo, Arias-Aranda et al., 2011; Wang et al., 2019). Also, different technological factors affect differently on BDA adoption among SMEs. Complexity and uncertainty and insecurity have a negative effect while trialability and observability have a positive effect. In contrast, relative advantage and compatibility show no effect. Both organizational factors, namely top management support and organizational resources, positively influence on BDA adoption among SMEs. On the other hand, external support is the only environmental factors that affect SMEs’ decision to adopt BDA, and the impacts of competitive pressure and government regulation are not supported. The study also concludes that BDA adoption has a significant positive influence on the financial performance and marketing performance of SMEs. Thus, investing in BDA by considering the influential TOE factors may enhance the financial performance and market performance of SMEs.

Appendix A

Big Data Analytics Adoption (Raguseo and Vitari, 2018)

Strategic Value

My company has used Big Data Analytics to……….

Respond more quickly to change.

Create competitive advantage.

Improve customer relations.

Transactional Value

My company has used Big Data Analytics to……….

Enhance savings in supply chain management.

Reduce operating costs.

Reduce communication costs.

Enhance employee productivity.

Transformational Value

My company has used Big Data Analytics to……….

Improve employees' skill level.

Develop new business opportunities.

Expand capabilities.

Improve organizational structure and processes.

Informational Value

My company has used Big Data Analytics to……….

Enable faster access to data.

Improve management data.

Improve data accuracy.

Technological Factors

Relative Advantage (Chen *et al.*, 2015; Ghobakhloo *et al.*, 2011a; Premkumar and Roberts, 1999)

Big Data Analytics improves the quality of work

Big Data Analytics makes work more efficient

Big Data Analytics lowers costs

Big Data Analytics improves customer service

Big Data Analytics attracts new sales to new customers or new markets

Big Data Analytics adoption identifies new product/service opportunities

Compatibility (Chen *et al.*, 2015; Ghobakhloo *et al.*, 2011a; Thong, 1999; Tornatzky and Klein, 1982)

Using Big Data Analytics is consistent with our business practices

Using Big Data Analytics fits our organizational culture

Overall, it is easy to incorporate Big Data Analytics into our organization

Complexity (Lai *et al.*, 2018; Xu *et al.*, 2017)

Learning to use the Big Data Analytics is difficult for employees

Big Data Analytics is difficult to maintain

Big Data Analytics is difficult to operate

Trialability (Etsebeth, 2013; Limthongchai and Speece, 2003; Moore and Benbasat, 1991)

My company could access to a free trial before making a decision to adopt Big Data Analytics

My company has the opportunity to try a number of Big Data Analytics applications before

making a decision and try out Big Data Analytics software packages on a s sufficiently large scale
My company is allowed to use Big Data Analytics on a trial basis long enough to see its true capabilities
It is easy to get out after testing a Big Data Analytics package
The start-up cost for using Big Data Analytics is low
Uncertainty and Insecurity (Salleh and Janczewski, 2016; Shin and Shin, 2011)
The need to outsource Big Data Analytics creates concerns on data security and privacy
The need to outsource Big Data Analytics creates vulnerability in access control of the organization's information asset
The need to outsource Big Data Analytics creates risks through excessive dependency towards vendor
The need to outsource Big Data Analytics complicates the process of implementing corporate policy in protecting individual privacy and data security
Observability (Limthongchai and Speece, 2003; Moore and Benbasat, 1991)
Many competitors or business partners in the market have started using Big Data Analytics
Using Big Data Analytics helps my company to connect with both domestic and international business partners
There are many computers that people in the company can access to Big Data Analytics
There are many computers that people in the company can access to use Big Data Analytics
Big Data Analytics shows improved results over doing business the traditional way

Organizational Factors

Top Management Support (Chen *et al.*, 2015; Lai *et al.*, 2018; Priyadarshinee *et al.*, 2017)
Our top management promotes the use of Big Data Analytics in the organization
Our top management creates support for Big Data Analytics initiatives within the organization
Our top management promotes Big Data Analytics as a strategic priority within the organization
Our top Management is interested in the news about using Big Data Analytics adoption
Organizational Readiness (Chen *et al.*, 2015)
lacking capital/financial resources has prevented my company from fully exploit Big Data Analytics
lacking needed IT infrastructure has prevented my company from exploiting Big Data Analytics
lacking analytics capability prevent the business fully exploit Big Data Analytics
lacking skilled resources prevent the business fully exploit Big Data Analytics

Environmental Factors

Competitive Pressure (Lai *et al.*, 2018)
Our choice to adopt Big Data Analytics would be strongly influenced by what competitors in the industry are doing
Our firm is under pressure from competitors to adopt Big Data Analytics
Our firm would adopt Big Data Analytics in response to what competitors are doing
External Support (Ghobakhloo *et al.*, 2011a; Ghobakhloo *et al.*, 2011b; Li, 2008)
Community agencies/vendors can provide required training for Big Data Analytics adoption
Community agencies/vendors can provide
effective technical support for Big Data Analytics adoption
Vendors actively market Big Data Analytics adoption
Government Regulation (Agrawal, 2015; Gupta and Barua, 2016; Lai *et al.*, 2018; Li, 2008)
The governmental policies encourage us to adopt new information technology (e.g., big data

analytics
The government provides incentives for using big data analytics in government procurements and
contracts such as offering technical support, training, and funding for big data analytics us
There are some business laws to deal with the security and privacy concerns over the Big Data Analytics technology

Firm Performance (Ji-fan Ren *et al.*, 2017; Raguseo and Vitari, 2018)

Firm Market Performance

Compared with your major competitors, how do you rate your firm's performance in the following areas over the past 3 years.

Entering new markets quickly.
Introducing new products or services to the market quickly.
Success rate of new products or services.
Market share.

Firm Financial Performance

Compared with your major competitors, how do you rate your firm's performance in the following areas over the past 3 years

Improving customer retention
Improving sale growths
Improving profitability

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